

11

Gaining Credibility Through Root-Cause Analysis and Exception Handling



Plurality which is not reduced to unity is confusion; unity which does not depend on plurality is tyranny.

BLAISE PASCAL (1623–1662)

This chapter introduces several analytical tools that are useful as regression model diagnostics and in situations where normality of the error distribution cannot be assumed. This chapter describes

- what role correlations and residuals play in validating modeling assumptions
- how elasticities, both own-price and cross-elasticity, are essential for understanding business growth as well as revenue-quantity relationships
- how a resistant measure of correlation can safeguard making unwarranted statements about causation
- why nonconventional methods are so important in improving the robustness of forecasting models in the face of uncertainty
- why forecast error patterns can give valuable insights into improving forecasting performance

The Diagnostic Checking Process in Demand Forecasting

Many demand planners and forecasters proceed by seeing how alike things are. Others proceed by trying to understand why things are different. The root-cause analysis of residuals and forecast errors is consistent with the latter approach. The diagnostic checking process is designed to reveal departures from assumptions about the underlying distribution of random errors and model formulation. It is an important phase for demand forecasters to learn about, as it can be a powerful visual tool for assessing the potential usefulness of a forecasting model, isolating and correcting unusual values, identifying hidden patterns, improving forecast accuracy, and understanding the nature or randomness in time series data.

A residual analysis may suggest nonlinear relationships, the need for transformations, or a better understanding of patterns and events that may not be transparent in the bulk of the unexplored data. Forecast error patterns can give valuable insights into improving forecast accuracy. And as we shall see, the unplanned findings of correlation analysis in regression modeling will often yield the most interesting and important results in a demand forecasting application.



The Role of Correlation Analysis in Regression Modeling

When demand forecasters have reason to believe that more than one factor (driver of demand) is required to solve a demand forecasting or econometric analysis problem, they turn to multiple linear regression models. To make forecasts with a multiple linear regression model, one needs to provide forecasts of more than one independent (explanatory) variable. When multiple variables are involved, the modeling effort can easily become more involved, so it is necessary to start with exploratory data analysis tools to get proper insight into the forecast-generating process.

By focusing only on the fit of the equation, you may discover a useful description of a forecast profile (*change*) but at the same time misspecify the uncertainty (*chance*), because error assumptions are needed in using the equation for forecasting. Also, accurate forecasts of the drivers of demand are needed, and if the underlying model errors are not normally distributed, as is usually assumed, there is a need for identifying root causes and exceptions. So there is always a trade-off between the goodness of fit and the quality of fit in the use of regression models for forecasting applications.

Recall, in a **multiple linear regression** (MLR) analysis, the deterministic component (*change*) takes the form of an equation,

$$\mu_{Y(X)} = \beta_0 + \beta_1 X_1 + \dots + \beta_k X_k$$

where X_1, \dots, X_k are k independent variables (or regressors), and $\beta_0, \beta_1, \dots, \beta_k$ are called **regression parameters**. This regression equation arises when the variation in the dependent variable Y is assumed to be affected by changes in more than one independent variable. Thus, the *expected (or average) value* of Y is said to depend on X_1, X_2, \dots, X_k . The dependence on X is henceforth suppressed in the notation; Let $\mu_{Y(X)} = \mu_Y$. In this case, one speaks of a multiple linear regression of Y on $X_1 \dots X_k$.

The regression equation is called a **model** when a random error (*chance*) term is added to the equation, which then becomes $Y = \mu_{Y(X)} + \varepsilon$, where ε commonly has an assumed normal error distribution.

While the formal theory of normal multiple linear regression analysis is extensive and is dealt with in many business statistics textbooks, of interest here are its application and interpretation in demand forecasting problems and those derivations and algorithms that are directly applicable to the interpretation of the analysis.

Adequacy of the model assumptions can be examined through a variety of methods, frequently graphical and mostly involving residuals (Actual minus Fit). One must be aware of a range of regression pitfalls to be avoided. These include trend collinearity, overfitting, extrapolation, outliers, nonnormal distributions, multicollinearity, and invalid assumptions regarding the model errors (e.g., independence, constant variance, and, usually, normality). Such inadequate assumptions often point to the root causes of not-so-credible forecasts.

But how does one put a model together? The first step in beginning a regression analysis for demand forecasting is to identify the drivers of demand—called factors—independent or explanatory variables that are believed to have influenced and expected to continue to influence the (dependent) variable to be forecast. The scatter diagram is a useful graphical tool for exploring the relationships among such factors.

The second step is to create a regression model by estimating the coefficients in the model by the method of least squares. This will give us a fitted equation from which we can determine the forecast profile.

Linear Association and Correlation

When the values of one time series (or variable) are paired with corresponding values of a related time series (or variable), a relationship between the variables can be depicted in a scatter diagram with one variable is plotted on the horizontal scale and the other is plotted on the vertical scale. Such a plot is a valuable tool for studying the relationship between a pair of variables.

When two series have a strong positive association, the scatter diagram reveals a pattern of points along a line of positive slope. A negative association shows up as a scatter pattern along a line with negative slope. A conventional measure of such linear association between a pair of variables Y and X is given by the *Pearson product moment correlation coefficient* r , where r is an averaging formula using the sample mean and sample standard deviation of the two variables, respectively.

The product moment correlation coefficient is a conventional measure of linear association between two variables.

Although forecasting and statistical software programs routinely calculate r , it is useful to view it as the result of an averaging process; namely, of the average of a product of standardized variables: Average $\{(Standardized Y_i) * (Standardized X_i)\}$, with a divisor of $(n-1)$ instead of n , where n is the common number of X, Y pairs. When a variable is standardized, it has a zero mean and a unit standard deviation, which is useful for making comparisons and correlations between variables that have very different sizes or scales of measurement.

A standardized value is obtained by subtracting the sample mean from the data and dividing by the sample standard deviation.

Figure 11.1 shows a spreadsheet calculation for obtaining the product moment correlation between annual housing starts and mortgage rates. The coefficient can vary between +1 and -1, so that $r = -0.20$ suggests a weak negative association between housing starts and mortgage rates.

Although the product moment correlation coefficient for housing starts versus mortgage rates data shown in the figure is only about -0.20 , the correlation coefficient for the respective annual change in these variables turns out to be -0.57 . Both are negative, as expected, but the latter reflects a much stronger linear association. This suggests that the strength of the relationship between housing starts and mortgage rates is reflected in their respective growth rates, not so much the actual levels.

The Scatter Plot Matrix

Creating scatter diagrams to validate a **linear association** between the dependent variable and each of the independent variables, as well as between pairs of independent variables, is an essential step in exploratory data analysis for larger datasets. Doing so can save you time when questions arise about root causes and exceptions with flawed models. At the same time, the diagrams can provide a better understanding of the data-generating process in the underlying relationships

Housing Starts	Mortgage Rates	Col 1 × Col 2
0.168898	-1.384396	-0.233822
-0.051812	-1.405769	0.072836
-0.217938	-1.410043	0.307302
-1.131335	-1.239058	1.401789
-0.755474	-1.157839	0.874718
-0.114703	-0.944107	0.108292
-0.235737	-0.589311	0.138923
-0.334226	-0.328558	0.109813
1.500873	-0.619234	-0.929391
2.403886	-0.679079	-1.632429
1.480404	-0.538016	-0.796480
-0.618717	-0.140474	0.086913
-1.144684	-0.123375	0.141226
-0.026003	-0.114826	0.002986
1.307751	-0.102002	-0.133393
1.406240	0.124554	0.175153
0.589850	0.620413	0.365951
-0.753694	1.377025	-1.037857
-1.370734	2.176384	-2.983244
-1.435998	2.330271	-3.346265
0.464958	1.312906	0.610447
0.602902	1.214589	0.732279
0.580060	0.876892	0.508650
0.768732	0.299815	0.230477
0.220219	-0.042157	-0.009284
-0.172550	-0.089178	0.015388
-0.504802	0.312639	-0.157821
-1.048865	0.274167	-0.287564
-1.577502	-0.012234	0.019300
0.000000	0.000000	$r = -0.201611$
1.000000	1.000000	

Figure 11.1 Calculation of the product moment correlation coefficient between annual housing starts and mortgage rates. (Source: Figure 7.12 Housing starts data; Figure 7.8 Mortgage rates data)

An arrangement of scatter diagrams between multiple pairs of variables is called the **scatter plot matrix**. We can summarize this by creating a correlation matrix of **product moment correlations** between pairs of variables.

The diagonal of a correlation matrix consists of 1s because each variable is perfectly correlated with itself. At the intersection of each row and column is the correlation coefficient relating the row variable to the column variable.

Because the matrix is symmetrical, it is useful to display the product moment correlation coefficient r on one side of the diagonal and an outlier-resistant version of correlation called r^* (SSD)—defined in the next section—on the other. To distinguish it from other types of correlation measures, the term ordinary correlation coefficient is here used interchangeably with the term Pearson product moment correlation coefficient.

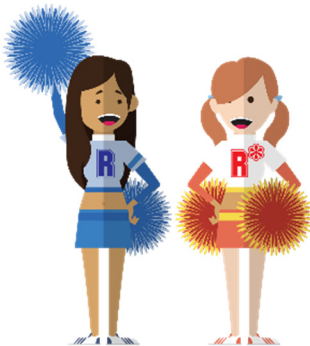
In this way, the demand forecaster gets the necessary insight from the augmented correlation matrix for constructing regression relationships. Contrasting r with r^* (SSD) may indicate departures from linearity due to outlying or non-typical data, so the demand forecaster then needs to review the underlying data for nonlinearity in the patterns. An outlier may not necessarily appear visually extreme from the bulk of the data in these situations.

A scatter plot matrix is an array of associations between pairs of variables.

The Need for Outlier Resistance in Correlation Analysis

The robust estimator of correlation, known as r^* (SSD), is less sensitive to outliers than the ordinary correlation coefficient r . It is derived from the standardized sums and differences of two variables, say Y and X , as introduced in a 1975 *Biometrika* paper entitled “Robust Estimation and Outlier Detection with Correlation Coefficients,” by Susan J. Devlin, Ram Gnanadesikan, and Jon R. Kettenring.

The first step in obtaining r^* (SSD) is to standardize both Y and X robustly by constructing two new variables \bar{Y} and \bar{X} :



$$\bar{Y} = (Y - Y^*)/S_{Y^*} \text{ and } \bar{X} = (X - X^*)/S_{X^*}$$

where Y^* and X^* are robust/resistant estimates of location and S_{Y^*} and S_{X^*} are robust/resistant estimates of scale.

Now, let $Z_1 = \bar{Y} + \bar{X}$ and $Z_2 = \bar{Y} - \bar{X}$, the sum and differences vectors, respectively. Then the robust variance of the sum vector Z_1 and difference vector Z_2 are calculated; they are denoted by V_{+}^* and V_{-}^* , respectively. These variances are used in the calculation of the robust correlation estimate r^* (SSD) given by

$$r^*(SSD) = (V_{+}^* - V_{-}^*) / (V_{+}^* + V_{-}^*).$$

The justification for this formula can be seen by inspecting the formula for the variance of the sum of two variables:

$$\text{Var}(Z_1) = \text{Var}(\bar{Y}) + \text{Var}(\bar{X}) + 2 \text{Cov}(\bar{Y}, \bar{X})$$

where Cov denotes the covariance between \bar{Y} and \bar{X} .

Because Y and X are standardized, centered about zero, with unit scale, the expected variance of Z_1 is approximately

$$\text{Var}(Z_1) \approx 1 + 1 + 2 \rho(\bar{Y}, \bar{X}) = 2(1 + \rho)$$

where ρ is the theoretical correlation between \bar{Y} and \bar{X} .

Similarly, for Z_2 ,

$$\begin{aligned}\text{Var}(Z_2) &\approx \text{Var}(\bar{Y}) + \text{Var}(\check{X}) - 2 \text{Cov}(\bar{Y}, \check{X}) \\ &= 1 + 1 - 2\rho = 2(1 - \rho).\end{aligned}$$

Notice that ρ is given by the expression

$$[\text{Var}(Z_1) - \text{Var}(Z_2)] / [\text{Var}(Z_1) + \text{Var}(Z_2)] \approx [2(1 + \rho) - 2(1 - \rho)] / [2(1 + \rho) + 2(1 - \rho)] = \rho.$$

Some robust estimates of the (square root of the) variance, required in the formula for r^* were discussed in Chapter 2; these include the unbiased median absolute deviation from the median (UMdAD = MdAD/0.6745) and the unbiased interquartile difference (UIQD = IQD/1.349).

Using Elasticities

In practice, it turns out that looking at correlations and linear relationships among transformed values of variables in a revenue demand model can also be very useful. For example, when using elasticities, the period-to-period changes (month-to-month, year-over-year, etc.) and percentage changes are often applied to time series modeling for a root-cause analysis.

Two important determinants of a firm's profitability—indeed its survival—are cost and the demand for its products or services. Demand must exist or be created if the business is to survive. It must also be high enough at least to cover fixed costs. Because of its key role, all business-planning activities require a careful analysis of demand over time. Demand forecasters also need to be aware of the relationship between quantity demanded and price.

Demand forecasters play an important role in helping to make pricing decisions by estimating price elasticities for products and services with regression models.

The complete chapter can be found in

Change & Chance Embraced

ACHIEVING AGILITY WITH DEMAND

FORECASTING IN THE SUPPLY CHAIN

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Contents



Chapter 1 - Embracing Change & Chance.....

Inside the Crystal Ball **Error! Bookmark not defined.**

Determinants of Demand	
Demand Forecasting Defined	
Why Demand Forecasting?	
The Role of Demand Forecasting in a Consumer-Driven Supply Chain	4
Is Demand Forecasting Worthwhile?	7
Who Are the End Users of Demand Forecasts in the Supply Chain?	8
Learning from Industry Examples	9
Examples of Product Demand	10
Is a Demand Forecast Just a Number?	11

Creating a Structured Forecasting Process 14

The PEER Methodology: A Structured Demand Forecasting Process	14
---	----

Case Example: A Consumer Electronics Company 15

PEER Step 1: Identifying Factors Likely to Affect Changes in Demand	16
The GLOBL Product Lines	17
The Marketplace for GLOBL Products	18
Step 2: Selecting a Forecasting Technique	19
Step 3: Executing and Evaluating Forecasting Models	22
Step 4: Reconciling Final Forecasts	22

Creating Predictive Visualizations 22

Takeaways 26



Chapter 2 - Demand Forecasting Is Mostly about Data:

Improving Data Quality through Data Exploration and Visualization28

Demand Forecasting Is Mostly about Data 29

Exploring Data Patterns	29
Learning by Looking at Data Patterns	30

Judging the Quality of Data 30

Data Visualization 35

Time Plots	35
Scatter Diagrams	36

Displaying Data Distributions 37

Overall Behavior of the Data	38
------------------------------	----

Stem-and-Leaf Displays	39
Box Plots	41
Quantile-Quantile Plots	43
Creating Data Summaries	44
Typical Values	44
The Trimmed Mean	45
Variability	45
Median Absolute Deviation from the Median	45
The Interquartile Difference	46
Detecting Outliers with Resistant Measures	47
The Need for Nonconventional Methods	48
M-Estimators	49
A Numerical Example	49
Why Is Normality So Important?	51
Case Example: GLOBL Product Line B Sales in Region A	52
Takeaways	54



Chapter 3 - Predictive Analytics: Selecting Useful Forecasting Techniques.....55

All Models Are Wrong. Some Are Useful	56
Qualitative Methods	56
Quantitative Approaches	59
Self-Driven Forecasting Techniques	60
Combining Forecasts is a Useful Method	61
Informed Judgment and Modeling Expertise	62
A Multimethod Approach to Forecasting	64
Some Supplementary Approaches	64
Market Research	64
New Product Introductions	65
Promotions and Special Events	65
Sales Force Composites and Customer Collaboration	65
Neural Nets for Forecasting	66
A Product Life-Cycle Perspective	66
A Prototypical Forecasting Technique: Smoothing Historical Patterns	68
Forecasting with Moving Averages	69
Fit versus Forecast Errors	71
Weighting Based on the Most Current History	73
A Spreadsheet Example: How to Forecast with Weighted Averages	75
Choosing the Smoothing Weight	78
Forecasting with Limited Data	78
Evaluating Forecasting Performance	79
Takeaways	79



Chapter 4 - Taming Uncertainty: What You Need to Know about Measuring Forecast Accuracy..... 80

<i>The Need to Measure Forecast Accuracy</i>	82
Analyzing Forecast Errors	82
Lack of Bias	82
What Is an Acceptable Precision?	83
<i>Ways to Evaluate Accuracy</i>	86
The Fit Period versus the Holdout Period	86
Goodness of Fit versus Forecast Accuracy	87
Item Level versus Aggregate Performance	88
Absolute Errors versus Squared Errors	88
Measures of bias	89
Measures of Precision	90
Comparing with Naive Techniques	93
Relative Error Measures	94
<i>The Myth of the MAPE . . . and How to Avoid It</i>	95
Are There More Reliable Measures Than the MAPE?	96
<i>Predictive Visualization Techniques</i>	96
Ladder Charts	96
Prediction-Realization Diagram	97
<i>Empirical Prediction Intervals for Time Series Models</i>	100
Prediction Interval as a Percentage Miss	101
Prediction Intervals as Early Warning Signals	101
Trigg Tracking Signal	103
<i>Spreadsheet Example: How to Monitor Forecasts</i>	104
<i>Mini Case: Accuracy Measurements of Transportation Forecasts</i>	107
<i>Takeaways</i>	112



Chapter 5 - Characterizing Demand Variability: Seasonality, Trend, and the Uncertainty Factor 114

<i>Visualizing Components in a Time Series</i>	115
Trends and Cycles	116
Seasonality	119
Irregular or Random Fluctuations	122
Weekly Patterns	124
Trading-Day Patterns	124
<i>Exploring Components of Variation</i>	126
Contribution of Trend and Seasonal Effects	127
A Diagnostic Plot and Test for Additivity	130
<i>Unusual Values Need Not Look Big or Be Far Out</i>	132
<i>The Ratio-to-Moving-Average Method</i>	134

Step 1: Trading-Day Adjustment	135
Step 2: Calculating a Centered Moving Average	135
Step 3: Trend-cycle and Seasonal Irregular Ratios	136
Step 4: Seasonally Adjusted Data	137
<i>GLOBL Case Example: Is the Decomposition Additive or Not?</i>	137
<i>APPENDIX: A Two-Way ANOVA Table Analysis</i>	139
Percent Contribution of Trend and Seasonal Effects	140
<i>Takeaways</i>	140



Chapter 6 - Dealing with Seasonal Fluctuations.....141

<i>Seasonal Influences</i>	141
Removing Seasonality by Differencing	143
Seasonal Decomposition	145
Uses of Seasonal Adjustment	146
<i>Multiplicative and Additive Seasonal Decompositions</i>	146
Decomposition of Monthly Data	146
Decomposition of Quarterly Data	151
Seasonal Decomposition of Weekly Point-of-Sale Data	153
<i>Census Seasonal Adjustment Method</i>	156
The Evolution of the X-13ARIMA-SEATS Program	157
Why Use the X-13ARIMA-SEATS Seasonal Adjustment Program?	157
A Forecast Using X-13ARIMA-SEATS	158
<i>Resistant Smoothing</i>	158
<i>Mini Case: A PEER Demand Forecasting Process for Turkey Dinner Cost</i>	162
<i>Takeaways</i>	168



Chapter 7 - Trend-Cycle Forecasting with Turning Points171

<i>Demand Forecasting with Economic Indicators</i>	171
Origin of Leading Indicators	174
Use of Leading Indicators	174
Composite Indicators	176
Reverse Trend Adjustment of the Leading Indicators	176
Sources of Indicators	178
Selecting Indicators	178
<i>Characterizing Trending Data Patterns</i>	180
Autocorrelation Analysis	180
First Order autocorrelation	182
The Correlogram	183

Trend-Variance Analysis	187
<i>Using Pressures to Analyze Business Cycles</i>	189
<i>Mini Case: Business Cycle Impact on New Orders for Metalworking Machinery</i>	191
1/12 Pressures	192
3/12 Pressures	193
12/12 Pressures	193
<i>Turning Point Forecasting</i>	194
Ten-Step Procedure for a Turning-Point Forecast	195
Alternative Approaches to Turning-Point Forecasting	195
<i>Takeaways</i>	196



Chapter 8 - Big Data: Baseline Forecasting With Exponential Smoothing

Models 197

<i>What is Exponential Smoothing?</i>	198
Smoothing Weights	199
The Simple Exponential Smoothing Method	201
<i>Forecast Profiles for Exponential Smoothing Methods</i>	202
Smoothing Levels and Constant Change	204
Damped and Exponential Trends	208
Some Spreadsheet Examples	210
Trend-Seasonal Models with Prediction Limits	216
The Pegels Classification for Trend-Seasonal Models	219
Outlier Adjustment with Prediction Limits	221
Predictive Visualization of Change and Chance – Hotel/Motel Demand	221
<i>Takeaways</i>	225



Chapter 9 - Short-Term Forecasting with ARIMA Models . 226

<i>Why Use ARIMA Models for Forecasting?</i>	226
The Linear Filter Model as a Black Box	227
<i>A Model-Building Strategy</i>	229
Identification: Interpreting Autocorrelation and Partial Autocorrelation Functions	230
Autocorrelation and Partial Autocorrelation Functions	231
An Important Duality Property	233
Seasonal ARMA Process	234
<i>Identifying Nonseasonal ARIMA Models</i>	236
Identification Steps	236
Models for Forecasting Stationary Time Series	236
White Noise and the Autoregressive Moving Average Model	237
One-Period Ahead Forecasts	239
L-Step-Ahead Forecasts	239
Three Kinds of Short-Term Trend Models	241
A Comparison of an ARIMA (0, 1, 0) Model and a Straight-Line Model	241
<i>Seasonal ARIMA Models</i>	244

A Multiplicative Seasonal ARIMA Model	244
Identifying Seasonal ARIMA Models	246
<i>Diagnostic Checking: Validating Model Adequacy</i>	247
<i>Implementing a Trend/Seasonal ARIMA Model for Tourism Demand</i>	249
Preliminary Data Analysis	249
Step 1: Identification	250
Step 2: Estimation	250
Step 3: Diagnostic Checking	251
<i>ARIMA Modeling Checklist</i>	254
<i>Takeaways</i>	255
<i>Postscript</i>	256



Chapter 10 - Demand Forecasting with Regression Models 258

<i>What Are Regression Models?</i>	259
The Regression Curve	260
A Simple Linear Model	260
The Least-Squares Assumption	260
<i>CASE: Sales and Advertising of a Weight Control Product</i>	262
<i>Creating Multiple Linear Regression Models</i>	263
Some Examples	264
<i>CASE: Linear Regression with Two Explanatory Variables</i>	266
<i>Assessing Model Adequacy</i>	268
Transformations and Data Visualization	268
Achieving Linearity	269
Some Perils in Regression Modeling	270
<i>Indicators for Qualitative Variables</i>	273
Use of Indicator Variables	273
Qualitative Factors	274
Dummy Variables for Different Slopes and Intercepts	275
Measuring Discontinuities	275
Adjusting for Seasonal Effects	276
Eliminating the Effects of Outliers	276
<i>How to Forecast with Qualitative Variables</i>	277
Modeling with a Single Qualitative Variable	278
Modeling with Two Qualitative Variables	279
Modeling with Three Qualitative Variables	279
<i>A Multiple Linear Regression Checklist</i>	281
<i>Takeaways</i>	282



Chapter 11 - Gaining Credibility Through Root-Cause

Analysis and Exception Handling 283

***The Diagnostic Checking Process in Forecasting*..... 284**

***The Role of Correlation Analysis in Regression Modeling* 284**

Linear Association and Correlation 285
The Scatter Plot Matrix 286
The Need for Outlier Resistance in Correlation Analysis 287

***Using Elasticities* 288**

Price Elasticity and Revenue Demand Forecasting 290
Cross-Elasticity 291
Other Demand Elasticities 292
Estimating Elasticities 292

***Validating Modeling Assumptions: A Root-Cause Analysis* 293**

A Run Test for Randomness 296
Nonrandom Patterns 297
Graphical Aids 299
Identifying Unusual Patterns 299

***Exception Handling: The Need for Robustness in Regression Modeling* 301**

Why Robust Regression? 301
M-Estimators 301
Calculating M-Estimates 302

***Using Rolling Forecast Simulations* 304**

Choosing the Holdout Period 304
Rolling Origins 305
Measuring Forecast Errors over Lead Time 306

***Mini Case: Estimating Elasticities and Promotion Effects* 306**

Procedure 308
Taming Uncertainty 310

***Multiple Regression Checklist* 311**

***Takeaways* 313**



Chapter 12 - The Final Forecast Numbers: Reconciling Change & Chance

..... 316

***Establishing Credibility* 317**

Setting Down Basic Facts: Forecast Data Analysis and Review 317
Establishing Factors Affecting Future Demand 318
Determining Causes of Change and Chance 318
Preparing Forecast Scenarios 318

<i>Analyzing Forecast Errors</i>	319
Taming Uncertainty: A Critical Role for Informed Judgment	320
Forecast Adjustments: Reconciling Sales Force and Management Overrides	321
Combining Forecasts and Methods	322
Verifying Reasonableness	323
Selecting 'Final Forecast' Numbers	324
<i>Gaining Acceptance from Management</i>	325
The Forecast Package	325
Forecast Presentations	326
<i>Case: Creating a Final Forecast for the GLOBL Company</i>	328
Step 1: Developing Factors	329
Impact Change Matrix for the Factors Influencing Product Demand	330
The Impact Association Matrix for the Chosen Factors	331
Exploratory Data Analysis of the Product Line and Factors Influencing Demand	332
Step 2: Creating Univariate and Multivariable Models for Product Lines	334
Handling Exceptions and Forecast Error Analysis	335
Combining Forecasts from Most Useful Models	337
An Unconstrained Baseline Forecast for GLOBL Product Line B, Region A	338
Step 3: Evaluating Model Performance Summaries	341
Step 4: Reconciling Model Projections with Informed Judgment	342
<i>Takeaways</i>	343



Chapter 13 - Creating a Data Framework for Agile Forecasting and Demand Management.....344

<i>Demand Management in the Supply Chain</i>	345
Data-Driven Demand Management Initiatives	346
Demand Information Flows	347
<i>Creating Planning Hierarchies for Demand Forecasting</i>	349
What Are Planning Hierarchies?	349
Operating Lead Times	350
Distribution Resource Planning (DRP)—A Time-Phased Planned Order Forecast	350
Spreadsheet Example: How to Create a Time-Phased Replenishment Plan	352
<i>A Framework for Agility in Forecast Decision Support Functions</i>	353
The Need for Agile Demand Forecasting	354
Dimensions of Demand	354
A Data-Driven Forecast Decision Support Architecture	355
Dealing with Cross-Functional Forecasting Data Requirements	358
Specifying Customer/Location Segments and Product Hierarchies	358
<i>Automated Statistical Models for Baseline Demand Forecasting</i>	360
Selecting Useful Models Visually	363
Searching for Optimal Smoothing Procedures	367
Error-Minimization Criteria	368
Searching for Optimal Smoothing Weights	368
Starting Values	368
Computational Support for Management Overrides	369
<i>Takeaways</i>	372



Chapter 14 - Blending Agile Forecasting with an Integrated Business Planning Process 373

PEERing into the Future: A Framework for Agile Forecasting in Demand Management 374

The Elephant and the Rider Metaphor	374
Prepare	374
Execute	376
Evaluate	376
Reconcile	381

Creating an Agile Forecasting Implementation Checklist 385

Selecting Overall Goals	385
Obtaining Adequate Resources	386
Defining Data	386
Forecast Data Management	387
Selecting Forecasting Software	387
Forecaster Training	388
Coordinating Modeling Efforts	388
Documenting for Future Reference	388
Presenting Models to Management	389

Engaging Agile Forecasting Decision Support 389

Economic/Demographic Data and Forecasting Services	389
Data and Database Management	390
Modeling Assistance	390
Training Workshops	390

The Forecast Manager's Checklists 391

Forecast Implementation Checklist	391
Software Selection Checklist	392
Large-Volume Demand Forecasting Checklist	393

Takeaways 394